Visualization of Environmental Factors Impacting COVID-19 as Researched in Literature

Background

The interdependence between climate, biodiversity, ecosystems, and human activity is recognized by the intergovernmental Panel on Climate Change IPCC and constitutes a basic criterion for assessing risks and impacts of climate change[1]. Research on the relation between infectious diseases and climate is well established as well. For example, the European Environment Agency EEA 2022 report on climate and health acknowledges the impact of global warming on the emergence and transmission of climate-sensitive infectious diseases and their outbreaks frequency[2]. Similarly, the global effect of climate change in accelerating the spread of infectious diseases is indisputable[3,4]. In the last three years, the emergence of the SARS-CoV-2 virus causing the COVID-19 global pandemic prompted research on the identification of the environmental data relevant to the study of COVID-19 and other infectious diseases[5], and on the connection between COVID-19 and the climate[6,7], and environmental and human factors such as pollution and infrastructure among others and COVID-19[8–12]. Additionally, understanding data within the social, political, cultural, and economic context[13] in the form of human-activity-related factors affecting the pandemic, highlights socio-ecological systems that not only affect the Earth, but also exacerbate inequality[14]. For example, Fish et al. (2021) exposed how sexual minority adults suffered disproportionate consequences in terms of mental health, physical health, quality of life, stress, and psychological distress[15]. Tai et al. (2020) investigated how African American, LatinX, and Native American communities' share of COVID-19 burden is excessive due to factors ranging from comorbidity exacerbated by poor living and working conditions and low access to healthcare, to discriminating institutional and societal factors[16].

Driven by the curiosity about the relationship between the COVID-19 virus and the environmental factors, whether meteorological, social, or health-related, that influence the viral spread, the following research question emerged: What did the literature on environmental factors affecting the COVID-19 pandemic reveal? What is the hierarchy of the relationship between the different factors? Establishing a correlation or a causation between climate change and COVID-19 is beyond the scope of this project. Nonetheless, putting the main factors affecting the pandemic as researched so far on the spotlight hopefully draws attention and awareness about their effects. By combining multiple data points from the literature into one infographic that visualizes the relationship between the pandemic and the environment, the shift towards the recognition of environmental determinants of health as parts of a collective system of natural and human created conditions[17], is highlighted, and the areas in need for more research can be identified.

Methods

To answer the research question, the researcher focused on four steps in the decision-making process: 1- data selection and analysis, 2- communication “angle” and framing, 3- visualization representation type, and 4- visualization coding.

1.The researcher conducted a literature review of dozens of texts starting with studies categorized as review articles[8–12], then adding relevant individual studies. The inclusion of literature reviews increases the representativeness of the data sample. The determining criteria for inclusion of the studies were appropriateness and authenticity[18] as well as reliability and trustworthiness of the studies[19]. Accordingly, the assessment of the studies was based on the following criteria: they are published in reputable journals, their research findings answer the visualization research question, they are as diverse as possible, and cover different geographical locations to reflect diverse climates and perspectives[20].

The researcher extracted the authors, publishing dates, and findings of the researched articles through content analysis and close reading, focusing on the result and discussion sections. Four main categories of environmental factors are identified: meteorological, socioeconomic, human activity related, and health related factors. After multiple rounds of data filtering and cleaning, 145 studies were included. The sample size was determined partly due to repetition of findings after the 145 threshold, and partly for allowing readability of the data on the visualization. Therefore, the scope of the visual is limited[18] only to the relation of COVID-19 with select environmental factors as revealed by a representative sample of the literature. Meteorological data are climate and weather related; socioeconomic data are related to GDP, population, and inequality issues; human-activity-related are caused by human and modernization; health-related factors are the ones involving the healthcare system and health outcomes. The inclusion decision of each factor under a specific category depended on the specific context of each factor. For example, despite age being a socioeconomic factor, in relation to COVID-19 age is a factor related to health outcomes and was categorized accordingly.

The collected data are in the form of study findings either confirming or denying the relationship between the investigated environmental factor and COVID-19-related measures such as transmission, mortality, cases, or other epidemiological measures. But because there is a significant variation in the methodologies used in each study, as outlined by Shakil et al. (2020)[9] (descriptive and trend analysis, comparative studies, linear regressions, Kendall and Spearman rank correlations, spatial analysis, among others), the findings are not comparable in their original form. To overcome this issue, the researcher resorted to magnitude coding, the practice of supplementing quantitative or qualitative data with an alphanumeric or symbolic code to indicate presence, frequency, intensity, or other attributes for describing the data[21].

The data are now categorical, and coded following three parameters, intensity, polarity, and measure. Intensity denotes how robust the finding is, it can take one of three values: significant S, weak, W, or insignificant I. Polarity denotes positive P, negative N, or relational R (not positive nor negative but still has a relation to the factor in question) with the COVID-19 epidemiological measures (transmission, incidence, etc.). By negative or positive the researcher means either inverse relation, or relation going in the same direction respectively. Finally, measure denotes epidemiological parameters of the virus, and they are narrowed down to three subgroups, transmission T, cases C, mortality M. Note that for practical purposes, the researcher resorted to some assumptions. For example, case fatality rate, a parameter used by

Sarmadi et al. (2021)[22] and others, is assumed to be equal to mortality; disease onset[23], PCR density[24], incidence[25], and prevalence[26] are assumed to equal to cases. The coded data findings basically take the following format: a combination of 1 to 4 letter codes, the first letter coding for intensity, the second for polarity, and the third for measure. For example, the code "SPM" indicates significant positive relation to COVID-19 mortality; the code "NT" indicates negative relation to COVID-19 transmission rate; "I" indicates insignificant relation; and so on and so forth. There are compound codes as well that code for factors that have relations to two or more epidemiological parameters. For example, NTM indicates a negative relation to both transmission and mortality.

2.Two key elements for determining the angle of a visualization are relevance and sufficiency. Relevance relates to the intended audience of the visualization, their interest in exploring it, them appreciating novelty of the work, and what message will be conveyed to them. Sufficiency relates to the number of angles needed to convey the message[27]. The visualization's researcher is communicating the right angle by addressing the intended audience of medical and public health professionals and communicators, presenting them with layers of environmental and COVID-19 data and their interrelations in one visualization that can be explored from different angles. The inclusion of the socioeconomic, human-related, and health-related factors not only increases the sufficiency and relevance of the visualization, it also enhances the ethical implications of the project[18].

Framing of the visualization relates to the decision on filtering the data[27]. Including too many data points may overwhelm the user of the visualization[28], excluding too many valuable data may sacrifice its message. Thus, only data that answer the research question is included in this visualization (author, publication date, environmental factors, and findings). Focus determines what part of the data takes precedence over another in terms of attracting attention first. The purpose of focus is to reduce noise[27], that is to present the information in different layers so viewers experience items in focus first then their attention goes to the second layer, then third, etc.

The focus of the dendrogram visualization is layered such that the connections and relationships occupy the first layer of focus, since the purpose of the visualization is to accentuate relationships between the COVID-19 virus and the environment it interacts with. The second layer of focus is the different environmental factors with their coded findings. The third layer is the frequency of each finding in the form of colored bubbles (called leaves in dendrograms) the size of which reflects the frequency of a coded relationship. The fourth layer is constituted by the names of the corresponding studies in the outermost layer of the circular dendrogram. The coded findings in the figure are supplemented with keys to avoid ambiguity, provenance is respected by referencing the included studies within the graph, and the hierarchy of the data points is accurately reflected in the graph.

3. The decision on the type of visualization that best reflects the data and the message is fundamental[29]. The choice of the circular dendrogram as the best graphical representation was informed by the nature of the data themselves. The data within the literature review exhibit

relations, correlations, and statistical significance, as well as hierarchies among the environmental factors (for example, under temperature there are subcategories of Normal, Average, Minimum, and Maximum), and frequencies (how many studies confirm a correlation between racial inequality and mortality rate, for instance).

A dendrogram is a diagram that displays categorical data in a hierarchical parent-child relationship, like a family tree structure, with data grouped into clusters according to a certain metric that determines proximity of data points[24]. A circular dendrogram displays the hierarchical layers of data in a circular format while striking a balance between function and form[28] by presenting a functional and aesthetically appealing visual that resembles the Corona virus itself. To increase data legibility[27], color hues are used to differentiate the different clusters of data in the dendrogram.

4. The data is collected in an Excel spreadsheet and converted to a comma separated value CSV file. Python code is used to build a hierarchical classification tree where the metrics and their respective relationships are defined. The hierarchal tree layout is based on the environmental factors: meteorological, socioeconomic, human activity, and health related topics as parent nodes. Once the tree hierarchy is completed, a JAVA Script Object Notation (JSON) file is generated by the Python code. The JSON file defines the hierarchy of the tree structure by designating the parent, inner (child), and outermost nodes (leaf) via the respective hierarchal relationship. The publicly available Vega Data Visualization software[30] is used to render the circular dendrogram graph as defined in the JSON file. Vega designates the leaf nodes of the tree to indicate the frequency of the occurrences of each coded classification (findings). Annotations are added in the form of labels on the nodes, the links, and the leaves to clarify the hierarchy. From the outermost leaf nodes, the study and the corresponding publishing date are attached.

Finally, the Vega software affords the dendrogram with some interactivity in the form of panning (moving around the display), zooming (in and out for closer or further view), rotating, and revealing annotations in a tooltip (hovering over the leaf to show annotation)[27] making it an exploratory visualization.

Results

Meteorological factors are by far the most researched (225 findings) categories, with temperature taking the lead (95 findings) followed by humidity (56 findings). Wind Speed is found in half of the studies 11/22 to increase transmission and/or cases, 6 /22 found the opposite effect, and the rest 5/22 found wind speed to be insignificant. Precipitation is found directly (positively) related to cases and/or transmission in 8/20 studies, insignificant in 7/20 studies, and inversely related to cases and/or transmission in 5/20. UV Light is found to decrease cases, transmission, and/or mortality in 8/14 studies, to be insignificant in 5/14 of the studies, and to increase transmission in one study. Atmospheric Pressure was found to decrease transmission in 3/6 studies, to increase transmission or cases in 2/6 studies, and to have insignificant effect in one study. Finally, Dew Point was found to increase cases in one study and to decrease cases in another. Within the temperature category, most findings show negative effect of temperature on cases and/or transmission of COVID-19, in line with the findings of most reviews. Some studies show an inverse effect of temperature, making a consensus on the effect of temperature difficult. At a more granular level, average temperature is the most researched (69 findings) while normal temperature is the least (1 study) in the project sample. The findings on the effects of average temperature are varied ranging between negative (inverse relation) and positive (direct relation); affecting transmission, cases, and/or mortality; and from significant, weak, to insignificant in intensity. Within the humidity category, relative humidity is the most researched (45 findings) with findings indicating insignificant effect on COVID-19 for the majority (9 studies), to almost equal number of studies finding direct and inverse effect on transmission (7 & 8 studies respectively), followed by 6 studies finding inverse effect of relative humidity on COVID-19 cases. Absolute Humidity was found to decrease cases and/or mortality in 6/9 studies, and to increase cases and/or transmission in 3/9 studies. Note that Evaporation is a factor with no data.

Factors relating to Human Activity are the second most researched among the categories identified by this project (72 findings), with Air Pollution accounting for most studied factors (44 findings). Pollutant Standard Index (PSI) accounts for the majority of studied sub-factors (34). Despite the variability in the PSI findings, the majority (30/34) indicates a positive (direct relation) to either cases, transmission, and/or mortality. Both Human Mobility and the Built Environment share equal number of 13 findings. Human Mobility is positively related in all studies to transmission and/or COVID-19 cases. The Built Environment factor seems to be positively related to COVID-19 transmission and/or cases except in one study[31] because the studied factor in this case is ventilation.

Socioeconomic factors rank third in our sample classification (62 findings) with an equal number of 13 research studies on effects of Population, Residence Pattern, and Racial Inequality, followed by Income Inequality and GDP per Capita (8 and 7 studies) respectively. Population number is found to increase cases, transmission, and/or mortality in all 13 studies. Residence Pattern is found to increase cases, transmission, and/or mortality in all 13 studies due to crowding. Racial Inequality is found to increase both cases and/or mortality in all 13 studies. Income Inequality is found to increase cases, transmission, and/or mortality in all 8 studies. GDP per Capita is found to increase cases in 3/7 studies, probably due to increased testing; and to decrease (2/7), not affect 1/7, or weakly affect cases and/or mortality for the rest of studies. Gender Inequality is the least researched socioeconomic factor found increasing either COVID-19 cases or transmission as presented in the project's sample.

Health factors constitute the fourth and last category (60 findings). Non-Pharmaceutical Interventions (NPI) is the most researched factor in the project's sample with an overwhelming negative (inverse) relation to cases and/or transmission (20/21) as findings. Comorbidity is directly related or positively associated with cases and/or mortality in 12/13 findings. Li et al., (2021a), however found a protective effect of HIV, influenza, and pneumonia prevalence due to possible cross immunity[32]. The Age factor shows 10/12 positive associations with cases and/or mortality. The negative association with Age was found by Okeahalam et al. (2020) who studied breastfeeding effects in infants[33], and by Li et al. (2021a) who researched effects of age under 10 on COVID-19 cases[32]. Health Inequality accounts for 6 of the findings under Health and shows positive association with cases, transmission, and/or mortality of COVID-19. Healthcare Capacity indicates negative association with mortality in 4/6 findings. One study, Meyer et al. (2020), found a positive association of Healthcare Capacity and cases, due to the association of healthcare capacity with early detection of cases and therefore increased number of cases[34]. Another, Lulbadda et al. (2021) found insignificant association[35]. Finally, Peckham et al. (2020) found that males are more prone to mortality from COVID-19 than females[36].

Discussion

The aim of this project is to present a visualization of COVID-19 pandemic in relation to environmental factors affecting its course. The choice of the environmental factors was based on the selected sample of studies and their findings. Environmental factors affecting the COVID-19 pandemic are numerous and varied. In this project, meteorological factors are found to be the most researched by scholars. However, focusing only on climate-related factors would undermine the message behind the visualization, thus the decision for inclusion of other factors. Human activity related factors emphasize the effects of modernity and pollution. Researching this category is crucial for future efforts in minimizing effects of climate change. Social and economic disparities make up substantial elements affecting the course of the pandemic and they can be researched more as reflected by the project sample. Lives could have been saved had racial, gender, and income inequalities did not play a role in the pandemic. Finally, research on health-related factors affecting the pandemic calls attention towards both effective measures for containment of the pandemic, and areas for improvements such as in the case of health inequality.

To realize the visualization, some assumptions were inevitable. For example, Air Pollution is used as an umbrella term for particles, toxic chemicals, etc. Pollutant Standard Index (PSI) is used as identified by Lorenzo et al. (2021)[37] and used for all studies that researched one or more component of the PSI (CO, NO2, O3, PM2.5, PM10 and SO2). Aerosol Optical Depth (AOD) is included with PSI findings. Comorbidity is assumed to include HIV, obesity, smoking, etc. Healthcare capacity includes number of nurses, beds, scans, O2 support, etc. Income inequality is assumed to include indices such as domestic income dispersion, ease of doing business, etc. Built Environment is assumed to include infrastructure, traffic structure, etc. Residence pattern is assumed to include population of urban people. Crowding is considered both under Built Environment and Residential Pattern. Some factors (longitude, latitude) were researched by some scholars included in the sample but are not presented in the visualization. This project does not present a comprehensive visualization on all environmental factors affecting the COVID-19 pandemic but provides a snapshot on literature findings on the pandemic and its related factors. Other areas that can be visualized in the future may be a dendrogram on the effects of COVID-19 pandemic on the environment (air quality after lockdowns, etc.), or the exploration of environmental factors that are overlooked by researchers.

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